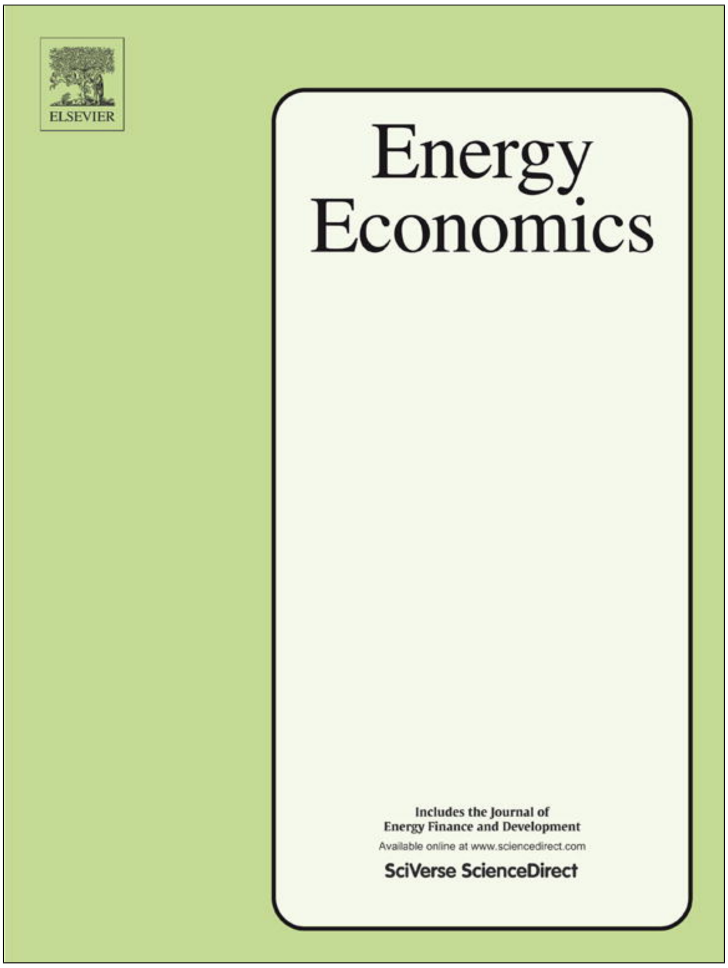
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Power TAC: A competitive economic simulation of the smart grid

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ABSTRACT

Sustainable energy systems of the future will need more than efficient, clean, low-cost, renewable energy sources; they will also need efficient price signals that motivate sustainable energy consumption as well as a better real-time alignment of energy demand and supply. The Power Trading Agent Competition (Power TAC) is a rich competitive simulation of future retail power markets. This simulation will help us to understand the dynamics of customer and retailer decision-making and the robustness of market designs, by stimulating researchers to develop broker agents and benchmark them against each other. This will provide compelling, actionable information for policymakers and industry leaders. We describe the competition scenario in detail, and we demonstrate behaviors that arise from the interaction of customer and broker models.

1. Introduction

Many of the sustainable energy resources (solar, wind, tidal, etc.) that could displace our dependence on fossil fuels are diffuse and do not necessarily produce power when it is needed. They are therefore difficult to integrate into our power grids and into their traditional control and capital structures. There have been many proposals to upgrade our electric power infrastructure into a “smart grid” (Amin and Wollenberg, 2005; United States Department of Energy, 2012) with components that can monitor energy usage in real time and help consumers better manage their energy usage. However, this is only the technical foundation. There is a clear need for new market structures that motivate sustainable behaviors by all participants. Energy prices that truly reflect energy availability can motivate consumers to shift their loads to minimize cost, and more effectively utilize distributed, small-scale energy storage and production resources (Joskow and Tirole, 2006). Unfortunately, it can be difficult to introduce creative and dynamic pricing schemes when energy is produced and sold by regulated monopolies, and transitions to competitive markets can be risky (Borenstein, 2002).

There is hope — energy markets are being opened to competition around the world in much the same way the telecom markets were opened in the 1990's (Lazer and Mayer-Schonberger, 2001). However, the scope of retail electric power markets is limited in the absence of smart metering infrastructure that allows a retailer to observe the consumption behavior of its customer portfolio, and where technical infrastructure does not effectively support energy storage and production in the retail (or “distribution”) domain.

Any serious proposal to change the way the electric power enterprise works must address several significant challenges:

Reliability: Frequency, voltage, and power factor must be closely managed to ensure safety and prevent outages.

Balancing: Supply and demand must be kept in balance, through a combination of supply and demand management.

Peak demand management: The need to serve peak demand that substantially exceeds steady-state demand drives investment in under-utilized supply and transmission resources.

Energy efficiency: Investment in demand reduction must be balanced against investments in production capacity.

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Externality reduction: Production of energy has been the cause of considerable environmental degradation and resource depletion, a cost that must be borne by future generations.

What is needed is a low-risk means for modeling and testing market designs and other policy options for retail power markets. We are addressing this need by organizing an open competition that will challenge participants to build autonomous, self-interested agents to compete directly with each other in a rich simulation focused on the structure and operation of retail power markets. The Power Trading Agent Competition (Power TAC) (Ketter et al., 2012b) is an example of a Trading Agent Competition[1] (Wellman et al., 2007) applied to electric power markets. It addresses important elements of the smart grid challenges outlined in Ramchurn et al. (2012), since many of these challenges involve economically motivated decisions of large numbers of actors. The Power TAC simulation can be used to evaluate a range of market-based approaches to addressing the challenges we have identified. It contains realistic models of energy consumers, producers, and markets, along with environmental factors, such as weather, that affect energy production and consumption. Alternative market mechanisms and policy options can be applied to the simulation model and tested in open competitions. Research results from Power TAC will help policy makers create mechanisms that produce the intended incentives for energy producers and consumers. They will also help to develop and validate intelligent automation technologies that can support effective management of participants in these market mechanisms.

The paper is organized as follows. In Section 2 we give an overview of the dominating Smart Grid challenges and related work regarding different simulation approaches. Section 3 describes the competition scenario in some detail, and Section 4 presents the simulation platform. In Section 5 we demonstrate the Power TAC platform and give an overview of pilot tournaments that took place in 2011 and 2012. We conclude with a call for participation in future Power TAC tournaments in Section 6.

2. Related work

2.1. Energy grids and markets

The power grid infrastructure today is largely organized as a strict hierarchy; at the high-voltage "transmission" level, a few centralized control centers manage relatively few large power plants and schedule their production according to market positions and energy demand forecasts. Demand forecasts typically come from historical consumption patterns and weather forecasts, and market positions arise from trading on day-ahead wholesale markets and from long-term contracts. Most buyers in these wholesale markets are "load-serving entities" (LSEs) who purchase power for delivery to their customers over local "distribution" grids. LSEs purchase (and sell) power for future delivery based on their own forecasts, and must ultimately balance supply and demand very closely. Any residual imbalances are dealt with through a "regulating market", which draws on a small subset of the total available production capacity that can be quickly ramped up or down to achieve balance. Prices in the regulating market are typically much less advantageous than short-horizon prices in the day-ahead market (Skytte, 1999). Traditionally, grid control is exercised primarily to adjust energy production to meet demand, on the assumption that demand can be influenced only by shutting off portions of it, either through imposing blackouts, or by exercising demand-management capabilities through "curtailments" in which selected loads, like large water heaters, can be shut off remotely for periods of time. Most customers get a monthly bill and have little or no awareness of how much power they are using at various times or for different purposes, or what it costs.

[1] See http://www.tradingagents.org.

Effective use of variable-output sources such as wind and solar will require that energy users adapt to the availability of sustainable power, and a pricing regime that reflects availability will motivate many households and businesses to invest in some combination of energy storage (e.g. thermal storage or batteries), demand management (e.g. price-sensitive appliance controls), and supply resources (e.g. solar panels). Retail-level supply resources will primarily consist of small, distributed and variable-output sustainable energy sources, and potentially large numbers of electric vehicle batteries will become available to buffer imbalances between supply and demand. These connect to the medium and low voltage "distribution" grid, and are outside the direct control of centralized management. In parallel, installation of smart metering equipment and demand side management devices (DSM) at customer premises will help customers monitor and actively manage their own energy usage (Gottwalt et al., 2011). Consequently, demand elasticity will increase and demand predictions via historical load profiles will become more difficult, especially as new types of tariff contracts become available in which prices vary by time or day, day of week, or dynamically to reflect the real cost of energy.

Electricity production and distribution systems are complex adaptive systems that need to be managed in real time to balance supply with demand within relatively tight bounds. Electricity markets are undergoing a transition from regulated monopolies to decentralized markets (Joskow, 2008), but so far the retail "aggregators" or "brokers" in these markets are almost entirely limited to purchasing power in the wholesale markets and delivering it to their customers; they have not had to deal with significant volumes of power production among their customers. Until the advent of "smart meters", neither retail power suppliers nor their customers have had the ability to understand which customers are consuming power at particular times, and since suppliers cannot charge for power usage on timescales finer than their meter readings, there has been no ability to expose customers to prices that reflect the real-time costs of power. The increasing deployment of supply resources on the retail grid is challenging the ability of the existing centralized control regime to maintain reliability of energy supplies. The "virtual power plant" concept (Pudjianto et al., 2007) is an approach that makes these distributed resources visible, if not fully controllable, by centralized control systems. A critical unanswered question is the extent to which self-interested behaviors of market participants can effectively supplement hierarchical control of the physical infrastructure to balance supply and demand in such an environment.

Smart meters, virtual power plants, and retail competition alone will not be sufficient to align the variable output of renewable energy sources with consumption patterns of a modern industrial society. In areas with large hydroelectric power availability, this can be done by coordinating the output of hydro resources with the availability of other renewable sources (Matevosyan and Söder, 2007). Other cases will require large-scale investment in energy storage (Beaudin et al., 2010), and possibly in additional transmission capacity (Sveca and Söder, 2003). Energy storage can also be provided by plugged-in electric vehicles (Kempton and Tomić, 2005), and by thermal energy storage capacity (Stadler, 2008). In Table 1, we summarize the main contributions of these elements of the Smart Grid with respect to the challenges identified in the Introduction.

Table 1
Smart grid elements.

Challenges	Smart grid elements				
	Smart metering	EVs	Storage & DSM	VPP	Retail competition
Balancing	+	+	+	+	+
Energy efficiency	+	+	+		+
Externality reduction		+	+	+	
Peak demand mgt.	+	+	+		+
Reliability			+	+	

Some proposals (Ramchurn et al., 2012) envision retail customers or their appliances directly participating in the wholesale power markets. However, these markets are not designed to provide power for immediate delivery, nor are they designed to deal with large numbers of small-scale participants. They primarily trade in future contracts, because most bulk power production comes from plants that cannot be quickly started up or shut down, and owners of these plants cannot afford to run them without firm commitments to consume their output. Failure to fulfill a contract (as either a consumer or producer) can be expensive, and prices are generally better for longer lead-times.

Retail brokers play the role of financial intermediaries, aggregating the demand (and production) of large numbers of customers, observing and predicting their aggregate consumption and production patterns, and actively participating in the wholesale markets to minimize their risk-adjusted costs. Such a broker, acting on behalf of a large number of individual customers, can provide power at a lower average price, while making a profit, than the individuals could on their own.

The performance of markets arises from the interaction of market design and the economically motivated behavior of participants; well-designed markets can effectively align social goals with the profit-motivated interests of private parties, by defining an appropriate set of rules and incentives (Krishna and Perry, 1997). However, the real-world performance of market designs can be difficult to predict, and serious market breakdowns such as the California energy crisis in 2000 (Borenstein et al., 2002) have made policy makers justifiably wary of experimenting with new retail-level energy markets.

Smart grid pilot projects (Hammerstrom et al., 2007) are limited in their ability to test system dynamics for extreme situations, such as loss of a major producer like the Fukushima nuclear plant. They also lack the competitiveness of open markets, because a single project consortium typically controls and optimizes the interaction of all parts of the pilot participants. Agent-based simulation environments have been used to study the operation of wholesale power markets (Somani and Tesfatsion, 2008), but these studies are limited in their ability to explore the full range of unanticipated self-interested or destructive behaviors of the participants.

2.2. Simulation approaches

There are many important open questions and research challenges posed by a power grid with large numbers of active participants; for an example, see Ramchurn et al. (2012). A number of these questions concern the structure of markets and the behaviors of market participants. Some of these can be addressed by game-theoretic analysis (de Weerdt et al., 2011), but many are sufficiently complex that they cannot be effectively addressed by formal methods. To address these more complex issues, a simulation-based technique known as Agent-based Computational Economics (ACE) (Tesfatsion, 2002) has been used to study electrical wholesale power markets, for an example see Nicolaisen et al. (2001), Peters et al. (2012, forthcoming), Reddy and Veloso (2011a), Sun and Tesfatsion (2007), and Weidlich and Veit (2008).

Like other Trading Agent Competition scenarios (Ketter and Symeonidis, 2012), Power TAC extends the ACE paradigm by creating a rich economic simulation and inviting research teams to develop their own software agents to play the role of power retailers in the simulation, and to enter them in annual competitions. The ongoing discussion of Smart Markets (Bichler et al., 2010) recommends rich market simulations such as Power TAC to validate market structures and to minimize real-world risks. Table 2, lists the challenges and the corresponding research techniques.

Table 2
Research techniques.

Challenges	Research techniques				
	Mechanism design	Operations research	ACE	Competitive simulations	Pilot projects
Balancing	+		+	+	
Energy efficiency					+
Externality reduction	+			+	
Peak demand mgt.		+		+	+
Reliability		+	+		

3. Competition scenario

The major elements of the Power TAC scenario are shown in Fig. 1. The scenario models a "liberalized" retail power market in a medium-sized city, in which users and small-scale producers of power may choose among a set of alternative power suppliers or brokers, represented by the competing broker agents. These choices are represented by "subscriptions" to the tariff contracts offered by the brokers. The brokers are self-interested, autonomous agents (Collins et al., 2009, 2010a), built by individual research groups to participate in the competition; the remainder of the scenario is modeled by the Power TAC simulation platform. In the real world, brokers could be energy retailers, commercial or municipal utilities, or cooperatives.

The simulation proceeds in a series of discrete "timeslots," each representing 1 h in the simulation world. A typical simulation runs approximately 1440 timeslots, or 60 days of simulated time. Time advances by one timeslot every five seconds, so a simulation completes in about 2 h. The five-second interval is intended to give broker agents enough time to update their models and make trading decisions for each timeslot.

The two-hour game length is long for a multi-round competition environment, but we have found that this is close to the minimum number of interactions brokers need to build and use effective machine learning models. Much longer simulations can be run if needed to satisfy specific research requirements.

The actual duration of the scenario is stochastic, to minimize the opportunity for brokers to exploit a predictable "end-of-game" situation that, while it might win tournaments, has little research value or relationship to the real world.

3.1. Customers and tariff market

Brokers interact through a retail "tariff market" with customer models that simulate the households and businesses of a small city. Some customers are equipped with solar panels and windmills, producing as well as consuming power. All customers are assumed to be equipped with smart meters and their consumption and production are reported every hour. Many customer models also include "controllable capacities" or demand-side management capabilities such as heat pumps or water heaters that can be remotely enabled or disabled to offset imbalances or control costs, in exchange for lower rates. Because controllable capacities can reduce costs significantly, brokers can offer special tariffs for them.

Customer models exhibit sensitivity to weather conditions (simulated using real data within the platform) and calendar factors such as day of week and hour of day. Fig. 2 illustrates the rich set of significantly correlated, yet distinct, consumption (positive capacity) and production (negative capacity) patterns that are generated by such models. The models employ a combination of fine-grained appliance-level simulation and coarse-grained statistical simulation. The illustration also highlights the typical scenario where consumption in a region is much larger than local production thus requiring brokers to obtain power from the wholesale market.

The models also respond to price changes (Gottwalt et al., 2011) and have a range of preferences over tariff terms. For example, some are willing to subscribe to variable-price tariffs if they have the opportunity to save by adjusting their power usage, while others are willing to pay higher prices for the simplicity of fixed-rate or very simple time-of-use tariffs. Many of the customer models are capable of adaptive capacity

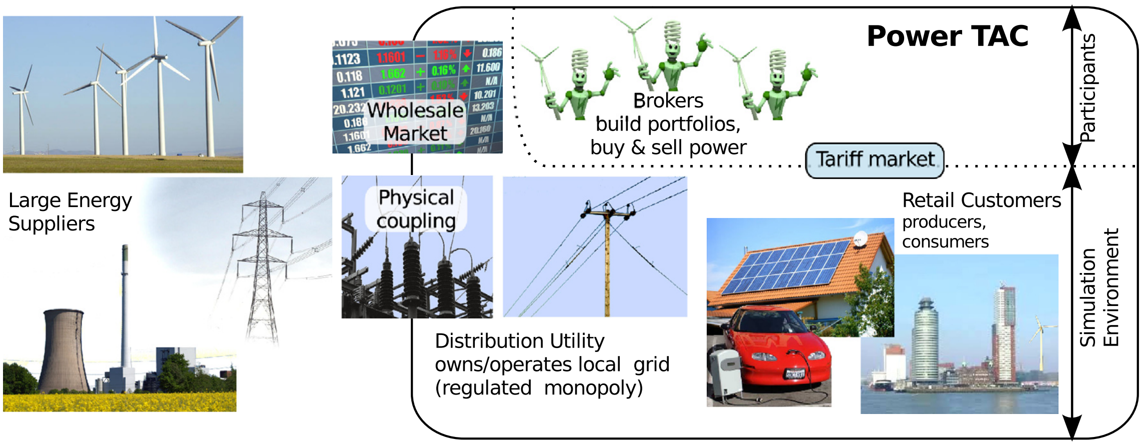

Fig. 1. Major elements of the Power TAC scenario. Brokers are the competitors, while the markets, customers, energy suppliers, and distribution utility are modeled by the simulation.

management, which allows them to evaluate various possibilities for capacity shifting and choose among the ones best suited to the applicable tariff rates, while also considering the potential choices of other customers that may be on the same tariff (Reddy and Veloso, 2012). This generates a flattening effect and avoids the problem of customers "herding" together, as seen from the aggregate consumption profile of 30,000 residential consumers in Fig. 3. Such "demand smoothing" is generally desirable to brokers, and it definitely can reduce peak demand, but on the other hand a more adaptive customer may behave in less predictable ways, thus adding to the challenges that need to be addressed by broker strategies in the competition.

Tariff contracts may include both usage-based and per-day charges, fixed and varying prices for both consumption and production of energy, rates that apply only above a specified usage threshold, signup bonuses, and early-withdrawal penalties. Separate contracts may be offered for charging electric vehicles, which could limit charging during high-demand periods, or even offer to pay the customer for feeding energy back into the grid at certain times. Variable prices may follow a fixed schedule (day/night pricing, for example), or they may be fully dynamic, possibly with specified advance notice of price changes.

The tariff market publishes new tariffs periodically to customers and to all brokers, typically 4 times per simulated day. This publication frequency represents a tradeoff between realism (most households do not receive mail so frequently) and providing adequate opportunity for brokers to observe customer behavior and attempt to deduce their preferences. Customers are notified of publication, and may choose to change their tariff subscriptions based on their preferences. Customer preferences include a number of factors, including cost and convenience, energy source, contract length, signup bonuses and withdrawal penalties, and inertia. The inertia factor means that only a fraction of customers will notice new tariff publications immediately. Customers must trade off cost and convenience when evaluating tariffs that include time-of-use or dynamic pricing, or discounts for participation in demand-side management schemes. As in the real world, customers are not completely rational, in the sense that they do not always choose the tariff with the best utility given their preferences.

3.2. Gencos and wholesale market

Brokers may buy and sell energy from retail customers, or they may buy and sell energy for future delivery in a wholesale market, which is modeled on real-world markets such as the European and North American day-ahead wholesale power markets. At any given time, brokers may place orders in the wholesale market to buy or sell power in 24 separate auctions, the first for delivery in the following timeslot, and the last 24 h in the future. Each active auction clears once

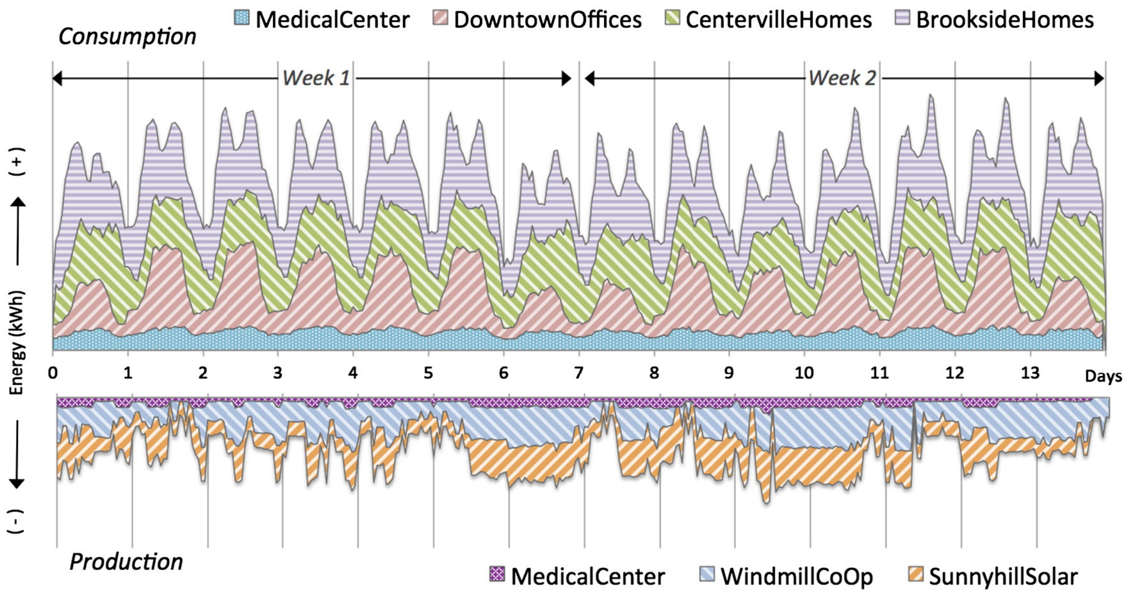

Fig. 2. Diverse consumption and production capacities from a range of customer models.

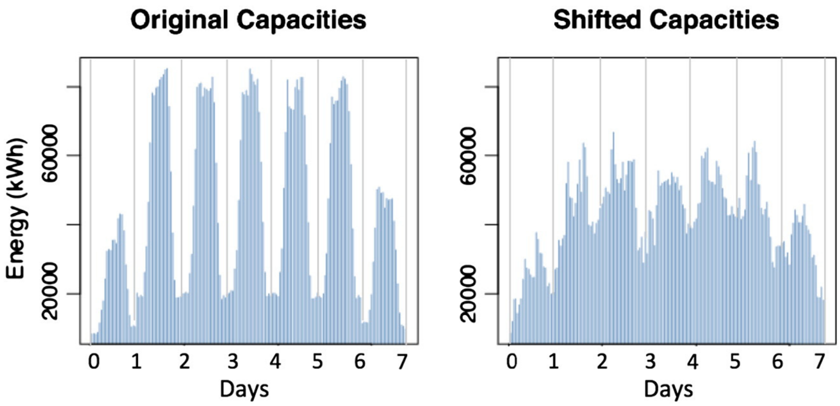

Fig. 3. Some customer models employ adaptive shifting algorithms to achieve capacity smoothing under variable-price broker tariffs.

per timeslot simply by sorting asks by ascending price, bids by descending price, and choosing a clearing price and volume halfway between the last ask and bid for which the bid price is higher than the ask price. The entire volume then clears at the chosen clearing price. For each of the 24 auction clearings in each timeslot, brokers are notified of the clearing price and volume, of their own updated market positions, and the bid and ask prices and volumes for the uncleared orders.

In addition to the brokers, the simulation includes “Genco” models to simulate utility-scale power suppliers who sell their output through the wholesale market. These suppliers represent different price points and lead-time requirements; for example, if a particular genco fails to sell any power in a particular timeslot, it shuts down, and may take between 1 and 8 h to restart. Therefore, while it is shut down, it only bids in auctions that are beyond its startup delay time. Shutdowns also occur randomly, at a low probability, for some of the genco models. In addition, the total capacity of each genco model varies somewhat through a mean-reverting random walk. These behaviors are not intended as high-quality models of utility-scale energy producers; their purpose is to provide some realistic unpredictability to wholesale prices. Also, there is an outside “buyer” in the market to provide liquidity. Its behavior is very simple; it always places one or more bids in each auction by choosing an exponentially distributed random price and a quantity inversely proportional to the price. This produces many low-priced, high-quantity bids, and a few high-priced, low-quantity bids, and limits extreme values caused by lack of liquidity. For example, there may be industrial operations that will buy large quantities of power at wholesale prices if it is less expensive than available alternative energy sources.

3.3. Distribution utility

The distribution utility (DU) models a regulated monopoly or government entity that owns and operates the physical facilities (distribution lines, transformers, etc.) and is responsible for real-time balancing of supply and demand within the distribution network. It does this primarily by operating in the “regulating market”, the real-time facet of the wholesale market, and by exercising demand and supply controls provided by brokers. The associated costs are allocated to the brokers responsible for the imbalance. In the real world, this balancing responsibility is typically handled higher in the grid hierarchy, by the Independent System Operator (ISO, North America) or Transmission System Operator (TSO, Europe). We have chosen to model the balancing behavior in the DU within the Power TAC simulation, partly because we are not modeling the upper levels of the hierarchy, but more importantly because we want to be able to study the potential role of retail brokers in the balancing process.

Within the simulation, the DU inspects the market positions of the brokers and the meter readings of the customers in each timeslot, and computes overall and per-broker balance between supply and demand. It then charges brokers a delivery fee for the use of its grid facilities, and a balancing fee (or payment) that covers its costs and guarantees that each broker would be better off, at least in expectation, by balancing its own supply and demand rather than relying on the DU (de Weerdt et al., 2011). If brokers have subscribers who have agreed to capacity controls, they may make offers to the DU for the right to exercise them if needed to reduce imbalances. These offers specify a price, and a proportion of actual demand (or production) against a particular tariff. The DU inspects the meter readings of the associated customers to determine the volume of energy available for each offer, then runs a VCG-based clearing algorithm (Clarke, 1971; Vickrey, 1961) to determine which offers to exercise and the associated payments. In this way, brokers can actually benefit in cases where their balancing offers are used to offset imbalances among other brokers.

The physical infrastructure of the grid is not modeled in the current version, because our focus is on the economic environment for a single distribution grid. It would be possible to couple the Power TAC simulation, or possibly multiple Power TAC simulations, with an existing physical simulation. This means, for example, that power factor is not modeled, and the distribution grid is assumed to be lossless. It also means that congestion is not modeled, but this is typically an issue with large-scale transmission grids, and less so with local distribution grids. However, congestion can have a major impact on the cost of power at particular points in the transmission grid, and this can be easily modeled by adjusting the capacity and pricing functions in the genco models.

3.4. Brokers

An overview of the interactions between a broker and the simulation environment during a single timeslot is shown in Fig. 4. At the beginning of each timeslot, wholesale orders that have arrived during the previous timeslot are cleared, and brokers receive records of cleared trades. They then receive the current weather report and a forecast for the following 24 h. This is followed by tariff publication (once every six timeslots) and interactions with customers. Once the customer models have run, the DU runs the balancing process and clears the balancing market. Finally, the accounting process gathers up all the transactions produced by the earlier steps, updates the brokers' cash balance, applies interest payments or charges, and forwards the transactions along with updated cash and market positions to the broker. This entire process is guaranteed to be completed at least 2 s before the start of the next timeslot.

This cycle and the two-second guarantee depend on simulation clocks in the simulation server and in the broker to be closely synchronized, a non-trivial problem given that the broker and server can be in any two locations on the Internet. This is accomplished by sharing offset and rate information between server and broker, and works as long as both systems are synchronized with the internet time standard.

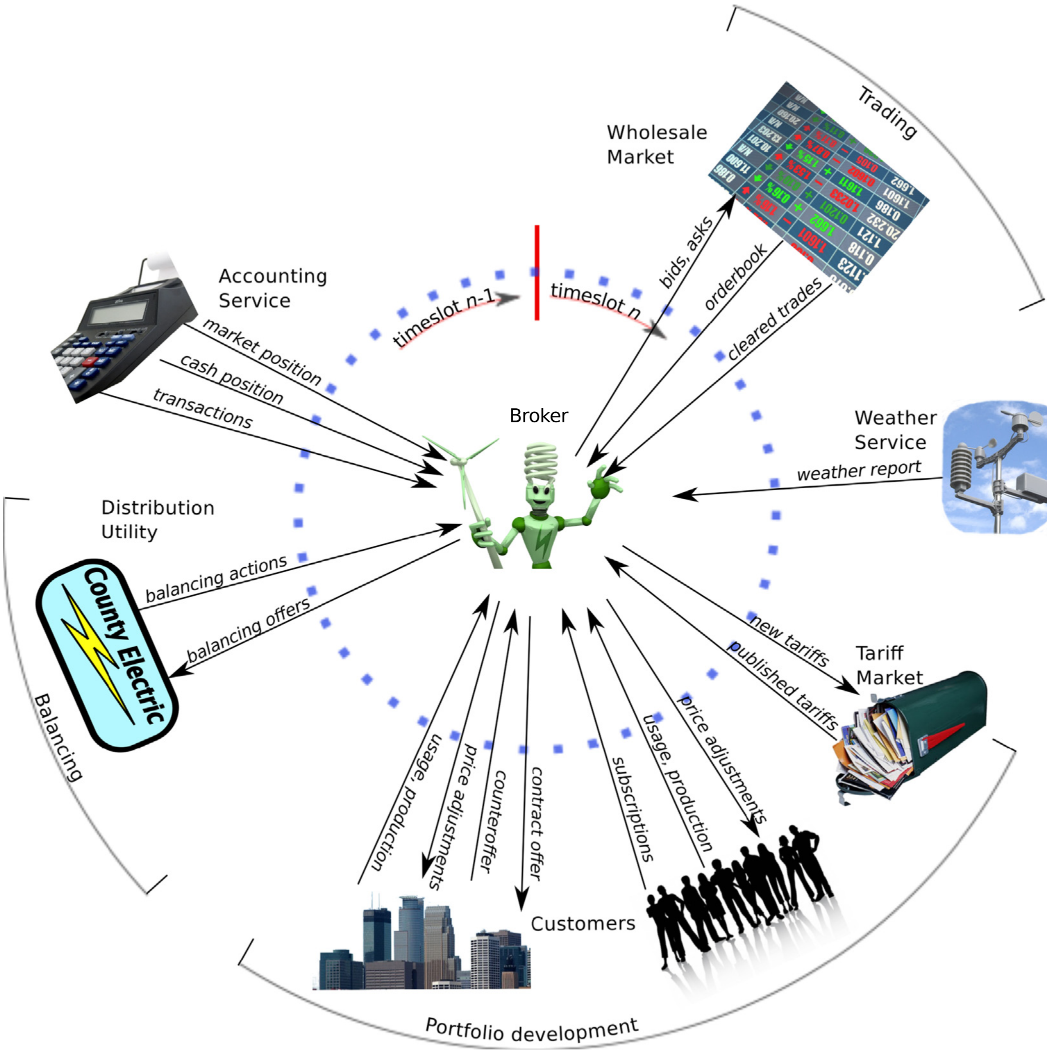

Fig. 4. Major interactions of a broker agent with the simulation environment within a single timeslot.

Brokers develop portfolios of customer contracts by offering tariff contracts to a population of anonymous residential and business customers, and by negotiating individual contracts with larger customers (such as major manufacturing facilities, or greenhouse complexes with many Combined Heat and Power (CHP) units). Because controllable capacities can reduce costs significantly, brokers can offer special tariffs for them, and then make offers to the DU for the right to exercise them to reduce imbalances. Tariffs need not be static; in addition to variable-rate tariffs, brokers have three ways to induce customers to switch from one tariff to another. First, they can offer more attractive tariffs, and wait for customers to discover them and switch. Second, they can specify an expiration date for a tariff, beyond which new subscriptions will not be accepted. Third, they can supersede an existing tariff with a new one, forcing customers to switch their subscriptions, although in this case customers have less inertia and are freed from early-withdrawal penalties, so there is some risk of losing customers in this case.

Given a portfolio of customer contracts, brokers also compete with each other in the wholesale market to minimize the prices they must pay for the power they deliver to their consuming customers, and to maximize the prices they receive for the power delivered to them by their producing customers.

Broker developers face a number of interesting challenges. Broker agents operate in a fast-paced information-rich environment. Customer behavior is stochastic, and depends partially on weather and the actions of brokers. Brokers are challenged to predict customer power usage and wholesale market prices up to 24 h in advance, and have multiple available actions to interact with the markets and influence customer behavior. The competitive environment is more or less oligopolistic, depending on the number of participating brokers. This means that broker actions have observable impacts on the competitive environment, and so accurate predictions may need to account for the effects of a broker's own actions in order to detect the effects of other brokers' actions (Ketter et al., 2012a). Successful broker agent designs will typically integrate a variety of techniques from artificial intelligence, machine learning, and game theory (Ketter and Symeonidis, 2012; Peters et al., 2012, forthcoming; Reddy and Veloso, 2011b).

3.5. Initial conditions

Brokers will likely need a significant amount of data to compose profitable tariffs and to guide their trading strategies. They could accumulate such data by observing the simulation for a period of time before offering tariffs and entering the market, but this would stretch the time required for a simulation run and would not be realistic. In the real world, a significant body of historical data on prices and consumption patterns is available to potential brokers before they enter the business. Therefore, we introduce two additional elements, essentially modeling the point in time when a market is opened to competition. The "default broker" plays the role of the incumbent regulated utility, which is typically the customer-facing side of the DU prior to the market opening. The simulation is run for a period in which the default broker has no competition, offers a simple fixed-price tariff to all customers, accumulates a smoothed time series of actual demand, and trades in the wholesale market using a simple trading strategy that is described in detail in the game specification (Ketter et al., 2012b). This "bootstrap" data on customer behavior and market prices is packaged and delivered to the competing brokers at the beginning of a simulation run, which conceptually starts immediately after the end of the bootstrap period in the simulation world.

4. Simulation platform

The simulation platform is a server that communicates with the competing brokers over the Internet. In a tournament environment, simulations are run with different numbers and combinations of broker agents, and the agent that is most profitable over a range of scenarios is the winner. In a research environment, the simulation may be configured in a number of ways to support different lines of research, such as achievement of socially desirable goals e.g. utilization of renewables, or the effects of varying levels of electric vehicle market penetration.

The Power TAC simulation platform is designed to serve as a rich and flexible foundation to address a variety of research questions, in addition to supporting an annual competition. It consists of a generic competitive simulation framework, a small set of core models including the tariff market and basic accounting, and a set of replaceable models. It can be configured to support individual research agendas as well as large-scale public tournaments. The wholesale market, distribution utility, balancing market, and customer and genco models are configurable and can be easily replaced. The customer and supplier models include "bottom-up" designs that explicitly represent appliances and people, along with "top-down" models that generate more or less realistic behaviors and preferences for large populations of households or businesses derived from customer surveys and pilot projects such as the EU project Cassandra-Energy.[2] Weather data is not currently generated by a model, but instead is pulled from historical records of weather reports and forecasts for a specific location. Wholesale power providers may be abstract models, or they may be interfaces for historical market interactions of real production facilities. This flexibility will allow Power TAC to model proposals for market designs, incentives, and taxes, or study the impact of increasing numbers of electric vehicles, or of wide adoption of price-sensitive "smart-grid" automation that could significantly change patterns of electric power usage.

In addition to the simulation server, the Power TAC platform includes three essential components to support competitions and research:

Tournament scheduler: A typical tournament involves multiple sets of simulation runs with different sets of brokers, and within a set the numbers and identities of brokers in each run need to be specified. In order to be able to make clear and fair performance distinctions among participating brokers, each competing broker must play every other broker, or every other subset of a given size, an equal number of times. Because simulation length is stochastic, and because the number of machines and brokers available to run simulations is constrained, the schedule is constructed and optimized on-the-fly to maximize resource utilization.

Sample broker: To minimize the effort required to build a competitive broker agent, we provide a simple but complete implementation of a Power TAC broker, modularized to separate the behavioral components (portfolio management, wholesale trading, etc.) from the message handling and interaction protocols between the broker and the simulation server and tournament scheduler.

Log analyzer: The simulation generates two log files as it runs: a "trace" log that describes briefly what is happening, and a "state" log that records all state changes in the simulation environment. The state log therefore contains all the data needed to understand exactly what happened and when during a simulation run. All the plots in this paper were produced from state log data. The log analyzer reads a state log and reconstructs the simulation environment at each point in the original simulation's timeline. Simple wrapper scripts can be written to extract and format the data needed for a particular study or plot.

The Power TAC platform is intended to support empirical research in addition to tournaments. Several features are implemented specifically for research purposes. The simulation server uses random values for a number of purposes in its various models, such as the process used by customer models to choose among nearly-equal tariff offerings. When the server starts up, it can read a file containing state-log entries from a previous game giving the seed values for each of the various random-value generators. If the file is not given, new random seeds will be generated and recorded in the state log. The tournament scheduler can be used to set up multiple-run experiments using repeated random sequences with different configurations of one of the agents, or different sets of agents, or changes in one or more of the models. In addition, the tournament scheduler gathers up the logs from each simulation, stores them, and makes them available through its web interface.

The Power TAC simulation server with all its models, as well as the sample broker, the log file analyzer, and the tournament scheduler, are available under a permissive open source license. Researchers are encouraged to download it and modify or extend it to serve their own research goals. For example, at least two research groups are primarily interested in the customer-modeling problem; they plan to run the simulation with a fixed set of competitive agents developed for the competition, and then modify and supplement the customer models to study ways that customer behaviors and technology investments affect their own outcomes as well as their impacts on the utilization of sustainable energy sources (Valogianni et al., 2012). Another group is building Power TAC broker agents that are augmented user interfaces for human decision-makers, to study the effectiveness of human decision-making with different sets of information display and decision-support tools (Verhagen et al., 2012). To support this type of study, the broker–server interaction can be configured to allow for a broker to "stall" the simulation clock at any time to allow a user to interact. Power TAC offers a generalized platform that can incorporate other models of interaction in the retail grid; for example, a virtual power plant can be viewed as a fully-cooperative portfolio of customers represented by their own virtual broker agent.

Power TAC will also be an effective teaching tool; students may be asked to build brokers or customer models, or to modify market and taxation rules and evaluate the impact on customers, brokers, or the relative value of sustainable energy sources with respect to fossil fuel-based suppliers.

5. Platform demonstration

We have hosted several competitions, including a pilot competition at the International Joint Conference on Artificial Intelligence (IJCAI) in Barcelona in July 2011 and demonstration competitions in June 2012 at the Autonomous Agents and Multi-Agent Systems conference in Valencia, and in September and December of 2012. Teams from Croatia (Matetic et al., 2012), Greece, Netherlands, UK, USA, Mexico, and Korea have developed and entered brokers for these tournaments.

Fig. 5 shows the observed clearing prices on the wholesale market for a period of 16 simulated days in one game from the September 2012 tournament. There is a slight diurnal pattern, but it is masked by considerable volatility over a range of nearly 5:1.

[2] http://www.cassandra-fp7.eu/.

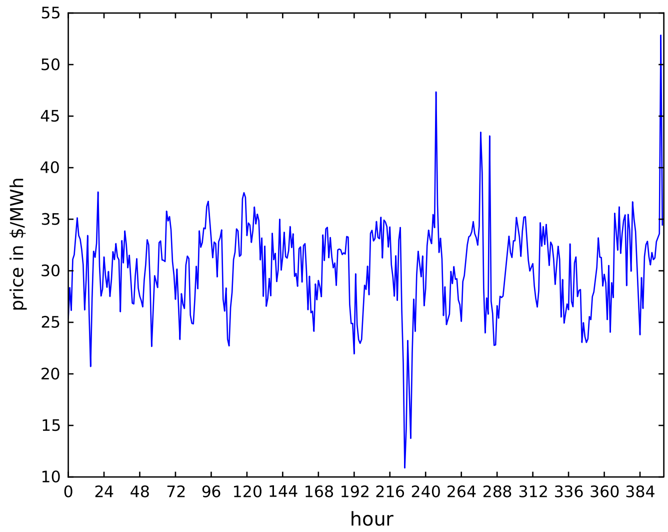

Fig. 5. Wholesale market clearing prices in the Fall 2012 competition demonstrate the volatility that must be anticipated by brokers.

Fig. 6 shows how a population of 30,000 customers from one consumer model were allocated to different tariffs over 40 days in one game from a 2012 demonstration competition. As new tariffs are introduced into the market by brokers, they often attract customers away from existing tariffs.

The competitions have also helped us identify weaknesses in the customer models and the balancing mechanism and proactively address those issues early in the development cycle. For example, the platform initially allowed brokers to publish variable price tariffs which only declare an expected price but are otherwise unconstrained. This allowed a broker to attract consumers using low expected price declarations who were then charged extremely high actual prices that did not average to the expected price. This led us to design additional constraints on variable price tariffs defining minimum/maximum price constraints; such evolutions of the tariff structure, brought on by game dynamics, also help inform real-world tariff design.

Another interesting finding in one competition was the strategy employed by a different broker. While the premise of the game relies on brokers trying to build balanced portfolios of supply and demand, this broker executed a highly profitable strategy by acquiring a large portfolio of only producers and selling the acquired power in the wholesale market, essentially forming a virtual power plant (Pudjianto et al., 2007). This is an ideal example of the unexpected strategies that are contributed through the competition, resulting in highly unpredictable emergent dynamics for the overall simulation.

6. Conclusion

Our energy-dependent society must adapt itself to more sustainable sources of energy. This will require a number of changes, including new market structures that motivate sustainable behaviors on the part of energy producers and consumers. It will also require us to make effective use of diffuse, volatile sources such as small-scale solar and wind installations, as well as small-scale energy storage capabilities such as electric vehicle batteries.

Competitive retail power markets have the potential to drive investment and behaviors that enhance sustainability. Power TAC is a rich competitive simulation of these future retail power markets. The competition will stimulate researchers to develop broker agents and benchmark them against each other and against the market structures embedded in the Power TAC scenario, helping us to better understand the dynamics of customer and retailer decision-making and the robustness of market designs, while providing actionable information for policymakers and industry leaders.

Power TAC is designed to support a research program centered around an annual tournament, a model that has been very effective in stimulating research. Prominent examples include RoboCup (Ros et al., 2009) and TAC (Ketter and Symeonidis, 2012).

Tournaments are typically held in conjunction with a relevant major conference where participants can present their work, discuss what they have learned, and begin planning for the next cycle. After a tournament, teams are encouraged to release their agent code (either binary or source), so that all teams can design and run their own experiments using a range of agent behaviors and market design details. Teams are then able to incorporate results of this research into their agent designs for the following year. Each year, the scenario may be updated to add new challenges, and if necessary to tune the market designs and level of realism, in order to enhance the relevance of the shared enterprise for both research value and policy guidance.

Power TAC models power markets primarily from an economic rather than from a physical viewpoint; it does not simulate the details of the physical infrastructure. In the future, we anticipate integrating

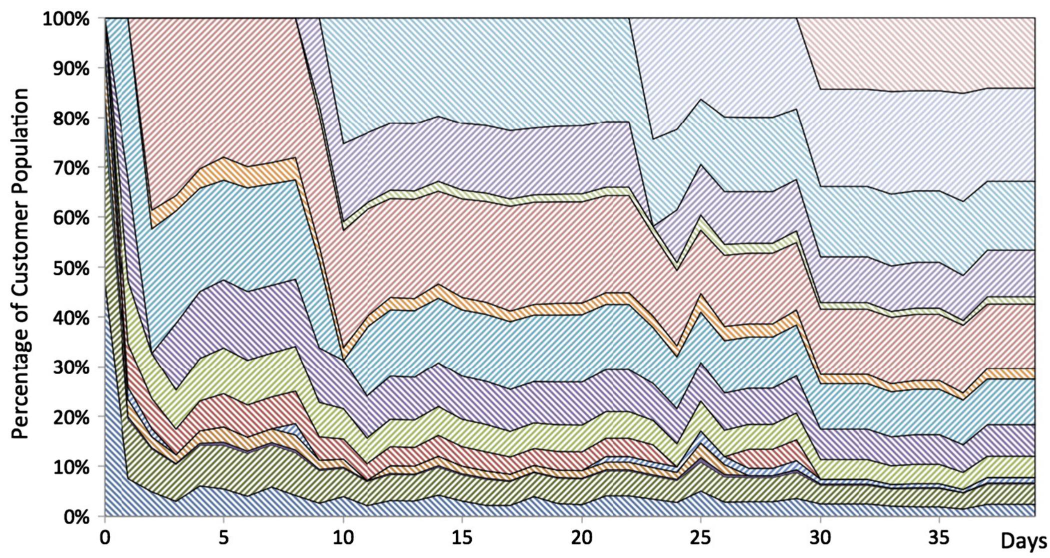

Fig. 6. This plot shows the varying allocation by percentage of a population of 30,000 residential consumers as new tariffs enter into the market over a period of 40 days.

the market simulation with a physical simulation in order to be able to evaluate the technical feasibility of the market's energy allocation over time.

Power TAC builds on the authors' extensive experience with the Trading Agent community and with the Trading Agent Competition for Supply Chain Management (TAC SCM) (Collins et al., 2010b). The strength of the world-wide TAC community is its individual research groups. Most are part of a university or business research organization. Due to the complexity of building a competitive autonomous agent, most groups are currently associated with Computer Science departments. Many existing teams have formed partnerships with business schools, economics departments, and electrical engineering departments. For the future, we are working on a broker framework that leverages a popular visual-programming system for building simulation models. We expect this will lower the barrier of entry for teams outside the computer science community.

Three Power TAC tournaments were held in 2012, to test and validate all components of the Power TAC platform. The "official" tournament for 2013 will be held in July in conjunction with the AAAI-2013 conference in Bellevue, Washington, USA. Other tournaments may be run if participants request them. Further information, including a detailed specification and development resources are available at http://www.powertac.org.

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